An Intelligent Gradient Detector for Monitoring of Passenger Flows

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Abstract

In this paper, we study the problem of monitoring of passenger flows. In particular, we consider an intelligent gradient algorithm to solve the problem.

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A large number of problems of technical vision extensively studied recently (see e.g. [1] – [4]). In particular, we can mention visual navigation in robotics (see e.g. [5] – [24]). In this paper, we study the problem of monitoring of passenger flows and consider an intelligent gradient algorithm to solve the problem. In particular, we use the following algorithm.

We consider video files that have been received from one bus camera. Our model uses an image of bus with only free chairs as the reference image $I_m$. First of all, the reference image should be recognized. In particular, areas of interest should be defined. We consider a video file as a sequence of images $I_{m_1}, \ldots, I_{m_n}$. 
Different gradient methods are quite frequently used in technical vision. In particular, we can mention Sobel filter and Canny edge detector. However, the effectiveness of these methods depends essentially on the noise level. Since in bus environment we have very high level of different noises, direct application of gradient methods give us very low level of recognition.

We consider standard gradient operator:

\[ \nabla f = \frac{\partial f}{\partial x} \hat{e}_x + \frac{\partial f}{\partial y} \hat{e}_y. \]

Application of \( \nabla f \) to different reference images and video files allows us to obtain two sets \( \mathcal{R} \) and \( \mathcal{V} \) where \( \mathcal{R} \) is the set of values of \( \nabla f \) for pixel of reference images and \( \mathcal{V} \) is the set of values of \( \nabla f \) for pixel of images from video files. We use a genetic algorithm for separation of \( \mathcal{R} \) and \( \mathcal{V} \) by multithreshold function. We denote our algorithm by \( CS[0] \). Let \( CS[1] \) be the algorithm \( CS[0] \) with intelligent visual landmarks model from [25].

In our experiments, we consider a sequence of files

\[ F[0], F[1], \ldots, F[11]. \]

We have obtained the exact number \( Num(F[i]) \) of passengers for each \( F[i] \) using visual observation. We consider only images \( F[i,j], 0 \leq j \leq 9 \), for each video file \( F[i], 1 \leq i \leq 11 \). For any image \( X \) and detector \( Y \), let \( R(X,Y) \) be the result of detection of passengers on the image \( X \) by the detector \( Y \).

Let

\[ N = \frac{\sum_{i=0}^{11} Num(F[i])}{12}. \]

In our case, \( N = 10.33 \). Let

\[ P[h] = \frac{\sum_{i=0}^{11} \sum_{j=0}^{9} R(F[i,j], H[h])}{120}. \]

where \( H[h] \) is a Haar cascade, \( 0 \leq h \leq 5 \), (see [25]). Let

\[ P[h+6] = \frac{\sum_{i=0}^{11} \sum_{j=0}^{9} R(F[i,j], S[h])}{120} \]

where \( h \in \{0, 1\} \). Selected experimental results are given in Figure 1.

Note that \( R(X,Y) \) includes some errors. Let \( L(X,Y) \) be the number of detections of passengers where they are not exist. Let \( M(X,Y) \) be the number of re-detections. Let

\[ L[h] = \frac{\sum_{i=0}^{11} \sum_{j=0}^{9} L(F[i,j], H[h])}{120}, \]
Figure 1: Comparison of $\mathcal{CS}$ and Haar cascades.

\[
M[h] = \frac{\sum \sum M(F[i, j], H[h])}{120},
\]

where $0 \leq h \leq 5$. Let

\[
L[h + 6] = \frac{\sum \sum L(F[i, j], \mathcal{CS}[h])}{120},
\]

\[
M[h + 6] = \frac{\sum \sum M(F[i, j], \mathcal{CS}[h])}{120},
\]

where $0 \leq h \leq 1$. Selected experimental results are given in Figure 2.

<table>
<thead>
<tr>
<th>$h$</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P[h]$</td>
<td>3.91</td>
<td>4.2</td>
<td>2.98</td>
<td>2.01</td>
<td>2.33</td>
<td>3.81</td>
<td>7.86</td>
<td>7.97</td>
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</table>

Figure 2: Comparison of errors of $\mathcal{CS}$ and Haar cascades.

Note that usage of the intelligent visual landmarks model from [25] allows us not only re-adjust reference images, but gives us information on frequency and values of changes of sets $R$ and $V$. We create a genetic algorithm based on this information for re-adjustment of the multithreshold function. Selected experimental results are given in Figure 3.

<table>
<thead>
<tr>
<th>$h$</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>$L[h]$</td>
<td>0.52</td>
<td>0.53</td>
<td>0.25</td>
<td>0.15</td>
<td>0.14</td>
<td>0.52</td>
<td>3.32</td>
<td>0.56</td>
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<tr>
<td>$M[h]$</td>
<td>0.56</td>
<td>0.2</td>
<td>0.13</td>
<td>0.05</td>
<td>0.05</td>
<td>0.37</td>
<td>0.2</td>
<td>0.28</td>
</tr>
</tbody>
</table>

Figure 3: The dependence of the quality of recognition from the number of generations of genetic algorithm for re-adjustment of the multithreshold function where we consider 1 as value for recognition with $\mathcal{CS}[1]$.

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References


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